

ORIE 5355

Lecture 17: Introduction to differential privacy

Nikhil Garg

Experimentation summary

- Classic A/B Test
- In social networks and marketplaces, *interference* ruins tests
 - Social networks: Social effect; Me getting treatment effects you
 - Marketplaces: Competition and scarcity introduces interference
- Experiments in the face of interference:
 - (Spatial or Graph-based) Cluster randomized assignment
 - Time-based experimentation: Switchbacks
- Causal inference without experiment: Synthetic control
- Naïve peeking in experimentation is bad, but can be done smartly

Introduction to (Differential) Privacy

(Special thanks for Juba Ziani, Georgia Tech, for slides)

Introduction: fundamental trade-off

Want to share and release information to do aggregate analyses

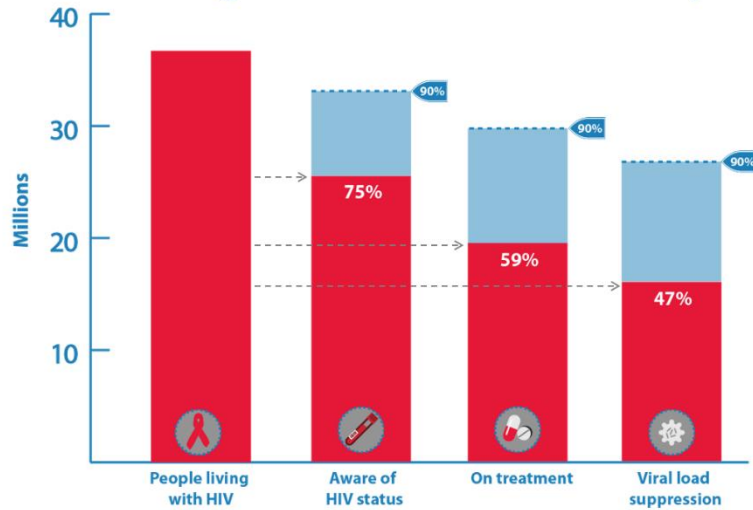
- Public audits (transparency)
- Want to help others do useful analyses (e.g., research reproducibility)
- Potentially legally mandated to share information (e.g., census)

Don't want to leak sensitive information about individuals

Problem: These two desiderata conflict, often in subtle ways!

Why is privacy important?

HIV testing and care continuum (2017)



Source: UNAIDS/WHO estimates



Dataset

Default of Credit Card Clients Dataset

Default Payments of Credit Card Clients in Taiwan from 2005

UCI ML UCI Machine Learning • updated 4 years ago (Version 1)

Data Tasks (1) Notebooks (270) Discussion (15) Activity Metadata

Download (1001 KB) New Notebook

Usability 7.1 License CC0: Public Domain Tags earth and nature, finance, e-commerce services

Dataset Information

This dataset contains information on default payments, demographic factors, credit data, history of payment, and bill statements of credit card clients in Taiwan from April 2005 to September 2005.

Failures of data privacy: anonymization

What is data anonymization?

Name	DOB	Gender	State/zip code	Has cancer?
Nikhil Garg	...	Male	NY 10044	No
Marge Simpson	04/19/1987	Female	SP 75234	No
Rick Sanchez	01/15/1943	Male	WA 98101	Yes
Misty	04/01/1983	Female	KT 16983	No

Failures of data privacy: anonymization

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Failures of data privacy: anonymization

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254jrtul42f4sf1	01/15/1943	Male	WA 98101	Yes
175dsa4f6jz68d	04/01/1983	Female	KT 16983	No

Failures of data privacy: anonymization

So what's the problem?

“Simple Demographics Often Identify People Uniquely”; Latanya Sweeney 2000

- A few attributes are enough to uniquely identify most of the US population
- (Zip, gender, date of birth) → identifies **87%** of US population
- What if I had this information (Zip, gender, date of birth) for much of the US?

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Failures of data privacy: anonymization

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- In Mass, some anonymized health care data was publicly available to researchers
- Sweeney spent **only \$20** for public DOB/gender/zip codes info in Cambridge. Bought voter rolls.
- Same birthday as the governor of Mass: 6 people in Cambridge
- Only 3 were male
- Only 1 had the right zip code
- ➔ Sweeney was able to ***uniquely identify the governor’s medical records!*** Sent them to his office.

This year: [“NYC Board of Elections glitch reveals how Mayor de Blasio’s son voted in city’s primary election”](#)

“Researchers with the Princeton lab were able to track down the results — which are supposed to be confidential — by cross-referencing state voter files against precinct-level results from election districts where only one voter is registered.”

The Netflix Competition

The image shows a screenshot of the Netflix website interface. At the top, there is a red navigation bar with the Netflix logo, links for 'Watch Instantly', 'Just for Kids', 'Taste Profile', and 'DVDs', and a search bar containing the text 'Movies, TV shows, actors, directors, genres'. Below the navigation bar, the 'TV Shows' section is visible. A red-bordered box highlights a sub-section titled 'Based on your interest in...' which contains two small movie posters: 'Doctor Who' and 'Drinking Buddies'. A red arrow labeled 'Inputs' points from this box to a larger green-bordered box containing a row of TV show posters: 'SHERLOCK', 'how i met your mother', 'New Girl', 'THE FOLLOWING', 'the office', and 'R...'. Below this row, another red-bordered box contains the text 'Because you watched DreamWorks Spooky Stories: Volume 2'. A red arrow points from this box to a green-bordered box containing a row of movie posters: 'SCARED SHREKLESS', 'idol', 'FLY ME TO THE MOON', 'TOON MATE'S FALL TREES', 'PARAMORMAN', 'CN COURAGE THE COWARDLY DOG', and 'TRAF...'. The word 'Recommendations' is written in green text below the second row of posters.

The Netflix Competition

How to improve recommendation system?

- Machine learning competition
- Try to predict user ratings from historical data as well as possible
- Provide “*anonymized*” data to participating teams

Netflix did more than just anonymization of data:

- Only small subsets of the full data; reduced the number of attributes
- Deleted some of the ratings
- Modified dates/temporal data

The Netflix Competition

“How To Break Anonymity of the Netflix Prize Dataset”, Arvind Narayanan and Vitaly Shmatikov, 2006

Only **2 weeks** after the Netflix competition

What they show:

Only need imperfect info:

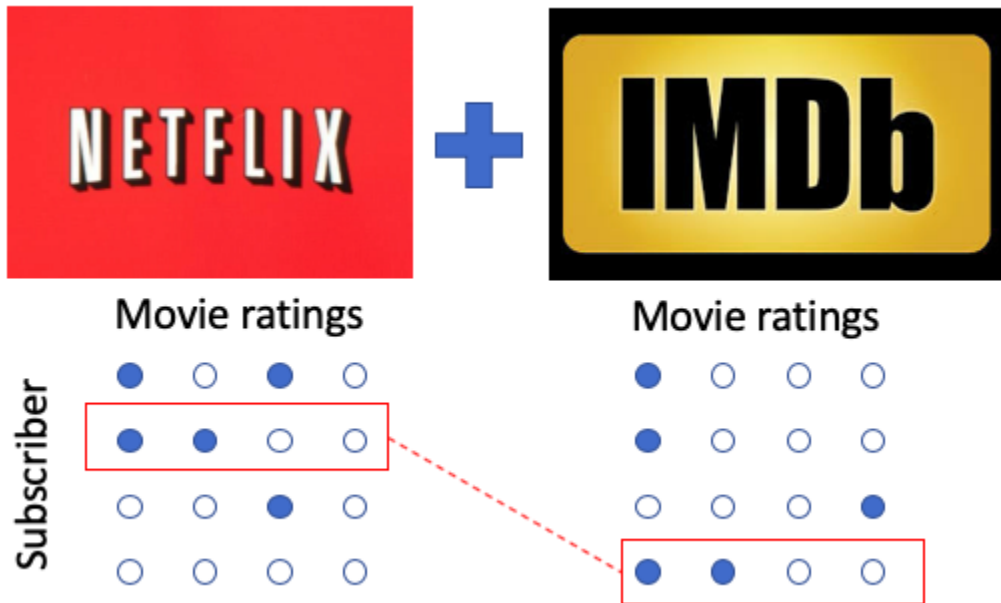
1. approx. dates of rating (± 2 weeks) for 6 movies
2. 2 ratings and dates (with a 3-day error)

Can uniquely identify the person:

1. 99% of the time
2. 68% of the time

The Netflix Competition

How did they do it?



Why is it bad?

- Netflix watch history: more expansive and private than IMDb public rating
- Link IMDb and Netflix profile → learn private watch history on Netflix
- Gay mother sued Netflix: watch history could reveal her sexual orientation to others

Privacy summary so far

Privacy is important, but trades off with other values

Idea: Do things to the data to preserve privacy before release

- Anonymization: remove personal identification
- Edit some of the entries a little bit
- Delete some entries

Even with above techniques, many privacy failures!

Common attack: Use *external* data (IMBb, voter file, etc) to extract more information from the anonymized data

Next idea: *Aggregate data before release*

Idea: Only release aggregated statistics/model.

Examples

- Population-level statistics such as averages, etc.
- Neural net (only see the final model, not the training data)

Why should it naively work?

- No individual-level details or features!
- Cannot identify a single row in a database: no access to such row-by-row data

Issue: If you release enough statistics, that's statistically identically to releasing the actual dataset

Data Aggregation fails! Example 1

How? For each “column” of the data, we have a summary statistic (mean). One column doesn’t tell us if any particular row is there. But if we have hundreds of thousands of columns in the dataset...

Example: genomic data

- Can you tell that someone’s data was in a DNA database, if all you have is allele frequency data from the database?
- Yes: “Resolving Individuals Contributing Trace Amounts of DNA to Highly Complex Mixtures Using High-Density SNP Genotyping Microarrays”, Homer et al., 2008

This is a problem

- Genomic data is more and more commonplace (ancestry tests, etc.)
- What if study only contains cancer patients/tries to link alleles to some rare disease? Can learn that you have a rare disease!

Data Aggregation fails! Example 2



WHEN YOU TRAIN PREDICTIVE MODELS
ON INPUT FROM YOUR USERS, IT CAN
LEAK INFORMATION IN UNEXPECTED WAYS.

[xkcd: Predictive Models](#)

“The Secret Sharer: Evaluating and Testing Unintended Memorization in Neural Networks”, Carlini et al., 2019

Predictive models tend to memorize:

- Imperfect generalization/overfitting to dataset
- More obvious in language models:
 - Work by memorizing characters/word associations
 - Can repeat word associations from training data

Potential attack:

- Predict next word: “My SSN is...”
- Recovers some SSN used in training data

Beyond aggregating: adding noise

Answering queries exactly is **not enough** for privacy, even if queries aggregate a lot of data (e.g., if release many columns in the dataset)

Natural next step:

- Do not answer queries exactly!
- Anonymize/aggregate, AND add noise/randomness to data or to queries

Q: Is this enough?

A: Yes!, but you have to be careful ***how and how much noise*** you add

Fundamental tradeoff: privacy vs accuracy

“Giving overly accurate answers to too many questions will inevitably destroy privacy.” -- Cynthia Dwork, Aaron Roth

- If you want to release a dataset that answers many questions about individuals, then you need to add more noise to each answer
- How much noise?

“Revealing information while preserving privacy”, Irit Dinur & Kobbi Nissim

Theorem: There exists a reconstruction attack that issues $O(n)$ (random) queries, obtains answers with **error αn** , and reconstruct the secret bits of all but $O(\alpha^2 n^2)$ users. **→ To protect privacy on most of the database against computationally efficient attacks, need noise of the order of at least $n^{1/2}$.**

Idea: [More] noise leads to [more] privacy

What happens if I probabilistically change the data?

Original Database D			Flip each datapoint with probability ϵ	Released database D'		
ID	Other Cols...	Has Cancer?		ID	Other Cols...	Has Cancer?
Nikhil	...	No	→	Nikhil	...	No
Rick	...	Yes		Rick	...	No
Homer	...	No		Homer	...	Yes

Distribution of outputs of computation ***almost unchanged*** (with small ϵ)

- If $\epsilon = 0$, then ***no privacy*** – we are releasing exact dataset
- If $\epsilon = \frac{1}{2}$, then ***no accuracy*** – learn nothing from the dataset

ϵ is a **policy choice**, not a technical one.

Can do the same thing with numeric columns

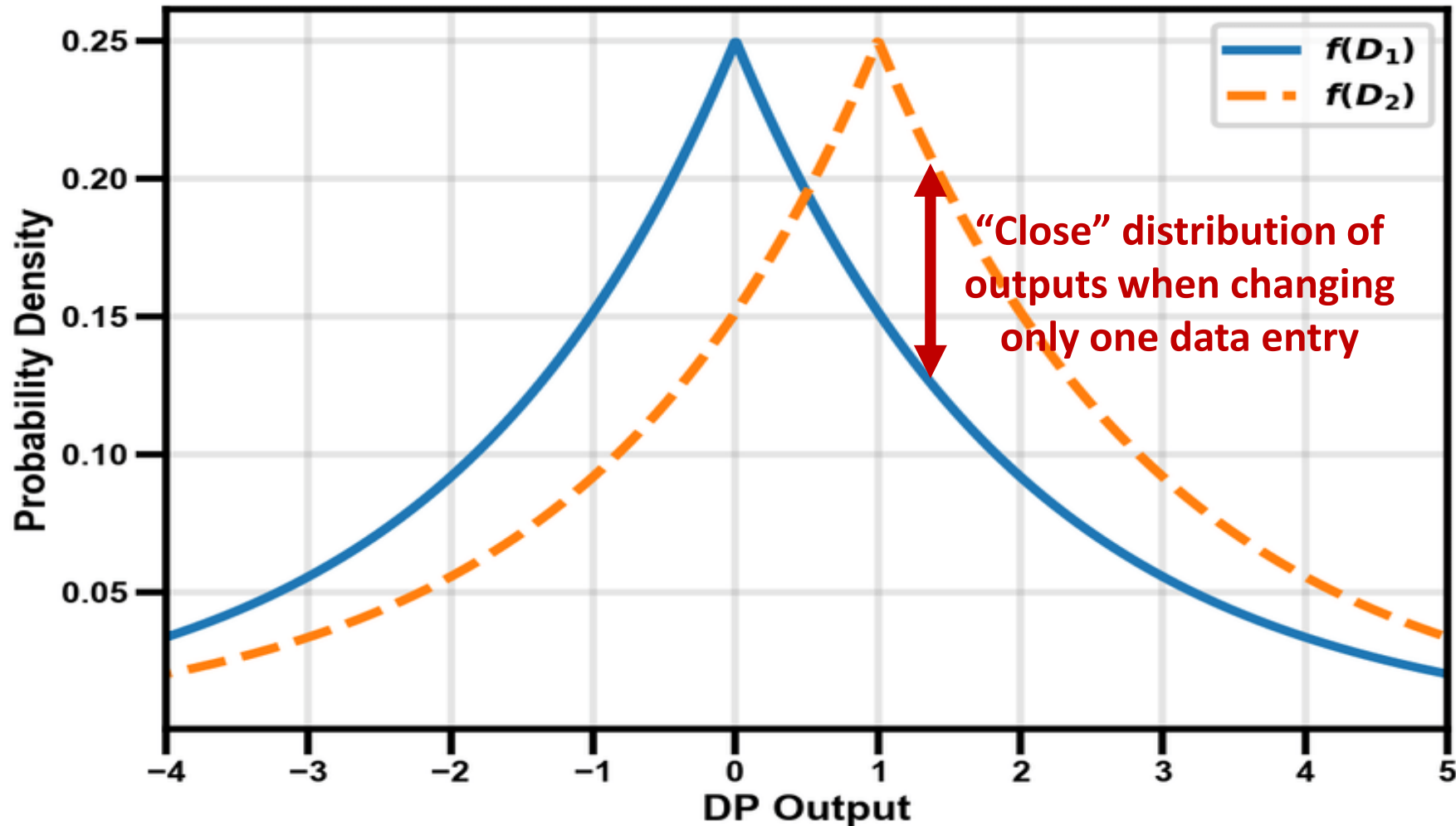


Image credit:
Juba Ziani,
Georgia Tech

Differential privacy

Differential privacy

- Fundamental limit: How much noise is needed
- Algorithm: What type (distribution) of noise to add

“Differential privacy is the only known framework to rigorously prevent such reconstruction attacks and privacy violations”

Now used in many places

- [Controversially] In the 2020 U.S. Census
- Google, Apple, Microsoft, LinkedIn...